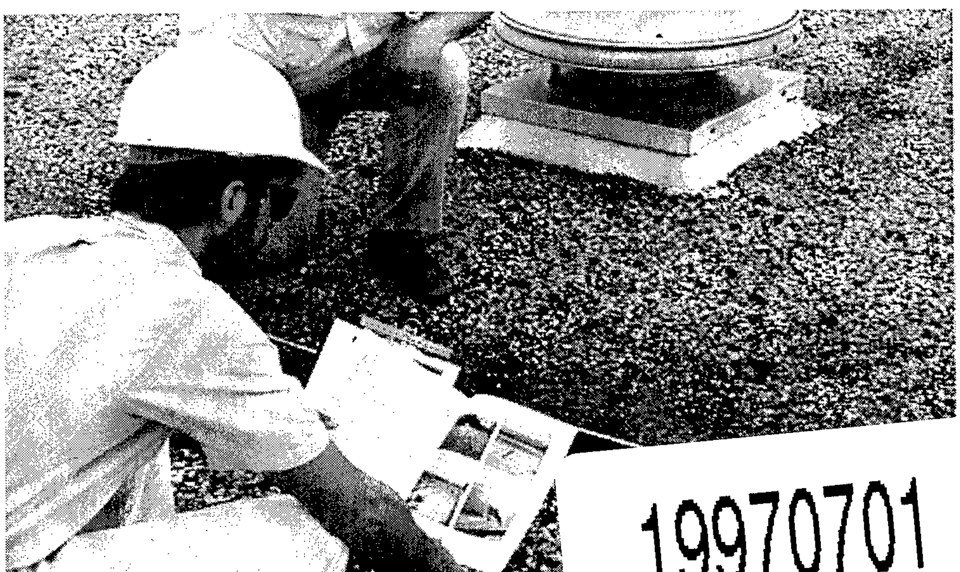
US Army Corps
of Engineers
Construction Engineering
Research Laboratories

USACERL Technical Report 97/83
June 1997

Statistical Analysis of ROOFER Database From 21 Army Installations

Assessment of Army Membrane Roofing Inventory and Effects of Various Factors on Roof Condition

by
David M. Bailey, Douglas G. Simpson, Xuming He, Olga Geling, Shun Lau, and Felicia Trachtenberg



The ROOFER Engineered Management System (EMS), developed by the U.S. Army Construction Engineering Research Laboratories (USACERL), enables Army installations to capture roofing inspection data in a single electronic database. The automated component of the EMS, called MicroROOFER, processes these data to help the user evaluate, prioritize, and budget roofing maintenance and repair needs.

To assist in developing future enhancements for ROOFER, USACERL acquired MicroROOFER databases from 21 Army installations that have implemented the ROOFER EMS. From these separate databases researchers created a master data set containing inventory data, inspection data, and condition indices for 3059 roofing sections. The researchers conducted a statistical analysis of the data set to characterize the inventory sample and determine how the roof condition depends on age and various design and construction factors. The data also were used to demonstrate the use of specially developed age/degradation curves for determining condition percentiles as functions of age.

The analysis confirmed that age is by far the most important predictor of roof section condition. Other influential predictors were surfacing, flashing type, drainage, and membrane type.

USER EVALUATION OF REPORT

REFERENCE: USACERL Technical Report 97/83, *Statistical Analysis of ROOFER Database From 21 Army Installations: Assessment of Army Membrane Roofing Inventory and Effects of Various Factors on Roof Condition*

Please take a few minutes to answer the questions below, tear out this sheet, and return it to USACERL. As user of this report, your customer comments will provide USACERL with information essential for improving future reports.

1. Does this report satisfy a need? (Comment on purpose, related project, or other area of interest for which report will be used.)

____

____

____

2. How, specifically, is the report being used? (Information source, design data or procedure, management procedure, source of ideas, etc.)

____

____

3. Has the information in this report led to any quantitative savings as far as manhours/contract dollars saved, operating costs avoided, efficiencies achieved, etc.? If so, please elaborate.

____

____

4. What is your evaluation of this report in the following areas?

a. Presentation: ______________________________

b. Completeness: ______________________________

c. Easy to Understand: ______________________________

d. Easy to Implement: ______________________________

e. Adequate Reference Material: ______________________________

f. Relates to Area of Interest: ______________________________

g. Did the report meet your expectations? ______________________________

h. Does the report raise unanswered questions? ______________________________

i. General Comments. (Indicate what you think should be changed to make this report and future reports of this type more responsive to your needs, more usable, improve readability, etc.)

5. If you would like to be contacted by the personnel who prepared this report to raise specific questions or discuss the topic, please fill in the following information.

Name: ____________________

Telephone Number: ____________________

Organization Address: ____________________

6. Please mail the completed form to:

Department of the Army
CONSTRUCTION ENGINEERING RESEARCH LABORATORIES
ATTN: CECER-TR-I
P.O. Box 9005
Champaign, IL 61826-9005

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. AGENCY USE ONLY *(Leave Blank)*	2. REPORT DATE June 1997	3. REPORT TYPE AND DATES COVERED Final

4. TITLE AND SUBTITLE
Statistical Analysis of ROOFER Database From 21 Army Installations: Assessment of Army Membrane Roofing Inventory and Effects of Various Factors on Roof Condition

5. FUNDING NUMBERS
MIPR
E87950435, dated 30 Sep 95

6. AUTHOR(S)
David M. Bailey, Douglas G. Simpson, Xuming He, Olga Geling, Shun Lau, and Felicia Trachtenberg

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
U.S. Army Construction Engineering Research Laboratories (USACERL)
P.O. Box 9005
Champaign, IL 61826-9005

8. PERFORMING ORGANIZATION REPORT NUMBER
TR 97/83

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
U.S. Army Center for Public Works
ATTN: CECPW-EB
7701 Telegraph Rd.
Alexandria, VA 22310-3862

10. SPONSORING / MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES
Copies are available from the National Technical Information Service, 5285 Port Royal Road, Springfield, VA 22161.

12a. DISTRIBUTION / AVAILABILITY STATEMENT
Approved for public release; distribution is unlimited.

12b. DISTRIBUTION CODE

13. ABSTRACT (Maximum 200 words)
The ROOFER Engineered Management System (EMS), developed by the U.S. Army Construction Engineering Research Laboratories (USACERL), enables Army installations to capture roofing inspection data in a single electronic database. The automated component of the EMS, called MicroROOFER, processes these data to help the user evaluate, prioritize, and budget roofing maintenance and repair needs.

To assist in developing future enhancements for ROOFER, USACERL acquired MicroROOFER databases from 21 Army installations that have implemented the ROOFER EMS. From these separate databases researchers created a master data set containing inventory data, inspection data, and condition indices for 3059 roofing sections. The researchers conducted a statistical analysis of the data set to characterize the inventory sample and determine how the roof condition depends on age and various design and construction factors. The data also were used to demonstrate the use of specially developed age/degradation curves for determining condition percentiles as functions of age.

The analysis confirmed that age is by far the most important predictor of roof section condition. Other influential predictors were surfacing, flashing type, drainage, and membrane type.

14. SUBJECT TERMS
ROOFER
Engineered Managment System (EMS)
maintenance and repair
membrane roofing

15. NUMBER OF PAGES
32

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	SAR

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std 239-18
298-102

Foreword

This study was conducted for U.S. Army Center for Public Works under Military Interdepartmental Purchase Request (MIPR) E87950435, dated 30 September 1995; Reimbursable Work Unit "Analyses of Existing ROOFER Databases for 21 Army Installations." The technical monitor was Fidel Rodriguez, CECPW-EB.

The work was performed by the Materials Science and Technology Division (FL-M) of the Facilities Technology Laboratory (FL), U.S. Army Construction Engineering Research Laboratories (USACERL). The USACERL Principal Investigator was David M. Bailey. A portion of the work was performed under task order with USACERL by Douglas G. Simpson, Xuming He, Olga Geling, Shun Lau, and Felicia Trachtenberg, University of Illinois at Urbana-Champaign.

Dr. Ilker R. Adiguzel is Acting Chief, CECER-FL-M, and Donald F. Fournier is Acting Operations Chief, CECER-FL. The USACERL technical editor was Gordon L. Cohen, Technical Information Team.

Dr. Michael J. O'Connor is Director of USACERL.

Contents

List of Tables and Figures

Tables

Figures

1 Introduction

Background

Army Directorates of Public Works (DPWs) face a difficult challenge in inspecting, evaluating, planning repair and replacement, and setting budget priorities for the large number of roofs on their installations. To enable DPW personnel to handle these tasks more efficiently and effectively the U.S. Army Construction Engineering Research Laboratories (USACERL) developed the ROOFER Engineered Management System (EMS). The ROOFER EMS applies repeatable inspection procedures, uniform condition indexes, standardized analytical methods, and computer automation to the development, scheduling, and budgeting of the installation's roof-management program (Bailey et al., 1989). Roofs are evaluated in *sections,* which are the individual management units for which condition data are collected. The automated component of the ROOFER EMS is MicroROOFER, a software package that includes an inventory database of the user installation's membrane roofs.

The data captured in MicroROOFER databases over the years provide an opportunity to investigate design and construction factors affecting the deterioration of the Army's bituminous built-up roofs and EPDM* roofing systems. USACERL has acquired 21 MicroROOFER databases from among the Army installations that have implemented the ROOFER EMS. These databases contain inventory tracking information, inspection data, and condition indexes for several thousand roof sections on Army installations.

Objective

The objective of this study was to conduct statistical analyses on 21 Army installation MicroROOFER databases to identify relationships between roofing design and construction factors, roofing age, and the condition of roofing system components.

---

* EPDM: ethylene-propylene-diene monomer.

Approach

Data from the 21 MicroROOFER databases were exported to a Microsoft Excel® spreadsheet and merged for statistical analysis. The SPSS statistical software package,* which can read Excel-formatted spreadsheets, provided the necessary tools for the statistical analysis. In the original MicroROOFER databases each inspected roof section had stored distress information with calculated index values for the membrane, flashing, and overall roof condition. (For further details on scoring standards see Shahin et al. [1987] and Bailey et al. [1993].) In the study reported here the membrane condition index (MCI), the flashing condition index (FCI), and the roofing condition index (RCI) were taken as response variables for multiple linear regression analysis. The insulation condition index (ICI) was not included in the study (see "Scope") below.

Potential regression variables included the age of the roof and numerous design and construction factors. These were screened using multiple linear regression analysis with stepwise variable selection. (For an introduction to multiple linear regression analysis see Weisberg [1985].) Following the regression analysis semi-parametric techniques were used to develop age-degradation-percentile curves. These curves concisely summarize the distribution of roof condition versus age while controlling for important factors.

Scope

As noted above, the MicroROOFER ICI data were not included in this study. The ICI, as defined by ROOFER, is determined by the moisture content of the insulation component when moisture has exceeded a threshold value. Moisture content normally passes the threshold value only after a membrane or flashing defect becomes severe enough to allow water to penetrate the roofing system. Unlike the MCI and FCI, the ICI does not normally degrade continuously over time from year zero because insulation is not directly exposed to the environment or rooftop traffic. Therefore, the ICI is not distinctively predictive with time.

The 21 installations participating in this study are identified in Table 1 (page 9). However, the identities of specific installations are masked in discussion of actual data (e.g., Table 8 and related text) to keep the focus on data analysis rather than the condition of any given installation's roof inventory.

* SPSS, Inc., 444 N. Michigan Ave., Chicago, IL 60611.

Mode of Technology Transfer

The results of this study provide the technical basis for developing more refined roof condition prediction models. These predictive models would be incorporated into the MicroROOFER software program. USACERL will work in support of the U.S. Army Center for Public Works (USACPW) to implement these enhancements of MicroROOFER into use at Army installations.

2 Data Selection and Characterization

Data Merging

ROOFER data were extracted from MicroROOFER databases as described in Chapter 1. The MicroROOFER software application is a specialized set of forms and reports that provide an interface with the Microsoft Access® relational database package. Within each ROOFER database the 'SectionCommon' tables contain the age and roof inspection data and the 'SectionLocal' tables contain data on construction and roof replacement.

An initial scrub of the 21 databases was performed to eliminate all roof sections that had areas less than 500 sq ft (46.45 m^2; 1 sq ft = 0.0929 m^2). These eliminated sections corresponded predominately to roofing over porches, breezeways, small canopies, and penthouses. The remaining data were exported to Microsoft Excel® and merged on the 'SectionKey' field. The resulting 21 files were then merged, giving a file with 8352 records corresponding to all the roof sections in the database. However, 3091 (or 37 percent) of these roof sections had not been inspected and therefore did not contain information on roof condition. These were excluded from the analysis, leaving 5261 remaining records.

For the purpose of this study, the analysis was restricted to roof sections with reported ages of 20 years or less. The age of each roof section was calculated from the date of construction or last replacement date and the date of inspection. As a whole, reported ages exceeding 20 years were considered unreliable based on examination of the data. As an example, in many of these cases a roof section's recorded date of construction was identical to the date of building construction which resulted in a roof age greater than 30 years and sometimes more than 50 years. Based on the industry-standard 20-year service life for these types of membrane roofing systems, these calculated roof ages are improbable.

Because the analysis is restricted to roofs no older than 20 years, predictions beyond 20 years are extrapolations and subject to model uncertainty. Of the 5261 records, there were 3068 roof sections with reported ages of 20 years or less. The analysis was further limited to roof sections of asphalt, coal tar pitch, or EPDM membrane. This criterion excluded nine more roof sections that had other types of membrane

(seven with bitumen type unknown; one with chlorinated polyethylene [CPE]; one with a polyvinyl chloride [PVC] type of membrane).

The final data set includes 3059 roof sections on 1178 buildings having a total roof area of more than 18 million sq ft (Table 1). Note that at the time the data were collected, some bases had few roof sections with both visual inspection data and construction/replacement history. Ten percent of the roof sections had areas less than 1,000 sq ft, 72 percent had areas between 1,000 and 10,000 sq ft, and 18 percent had areas greater than 10,000 sq ft.

Preliminary Analysis of Roof Age

Age is clearly a factor in the condition of a roof. Table 2 compares MCI, FCI, and RCI for roof sections aged 20 years or less and roof sections with unknown dates of construction and replacement. The table gives means and standard deviations in

Table 1. Roof sections comprising final data set.

Installation	Buildings	Total Area Roof	Roof Sections	Percent of Total Sections
Aberdeen PG	50	709,830	139	4.5
Bayonne MOT	15	804,373	64	2.1
Fort Belvoir	49	954,427	150	4.9
Fort Bragg	8	148,613	29	0.9
Fort Carson	101	1,990,946	268	8.8
Corpus Christi AD	15	758,397	73	2.4
Fort Detrick	5	69,533	7	0.2
Edgewood Arsenal	24	178,192	48	1.6
Fort Benning	129	2,281,888	377	12.4
Fort Bliss	166	1,760,150	396	12.9
Fort Riley	129	1,714,666	307	10.0
Fort Lee	5	77,493	11	0.4
Fort Leonard Wood	79	645,111	118	3.9
McCalester AAP	8	42,840	16	0.5
Fort Meade	63	1,226,008	158	5.1
Fort Sill	42	937,712	162	5.3
Twin Cities AAP	12	324,047	38	1.2
Tobyhanna AD	18	529,512	49	1.6
Watervliet Arsenal	15	685,479	78	2.5
White Sands MR	206	1,749,068	406	13.3
West Point MA	39	66,0401	165	5.4
TOTAL	1178	18,248,686	3059	

Table 2. Analysis of mean condition scores for roof sections of unknown age.

	Count	Mean RCI	Mean MCI	Mean FCI
Age Unknown	811	64.5 (±20.3)	77.8 (±21.2)	58.5 (±24.0)
Age ≤ 20	3,059	71.4 (±17.3)	82.2 (±18.3)	67.0 (±20.7)
Note: Numbers in parentheses are standard deviations.				

each category. The substantially lower mean condition indices in the age-unknown category suggest that many of these are older roofs.

To provide a preliminary indication of the age effect, Figures 1-4 show histograms of RCI for 5-year age intervals (i.e., 0-5, 6-10, 11-15, and 16-20). The condition ratings used in the histograms correspond to the ranges of scores shown in Table 3; see Bailey et al. (1989) for further details. Comparing the histograms for different age ranges reveals a clear trend. The distribution of the RCI is

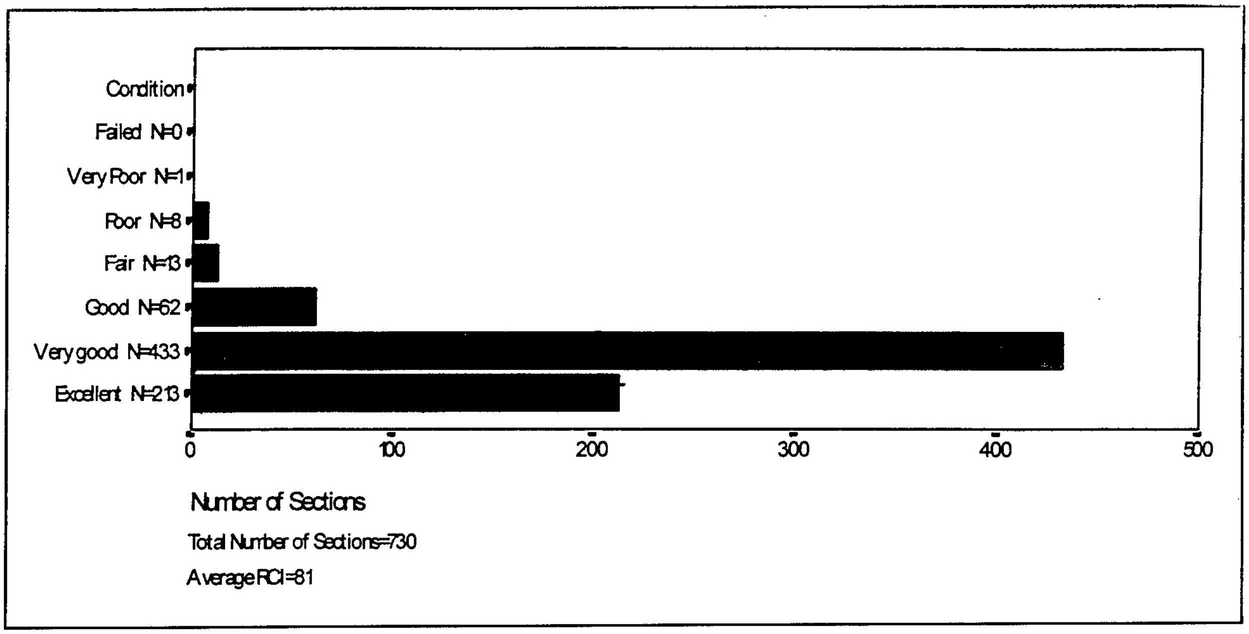


Figure 1. RCI frequency histograms for roof sections 0 to 5 years old.

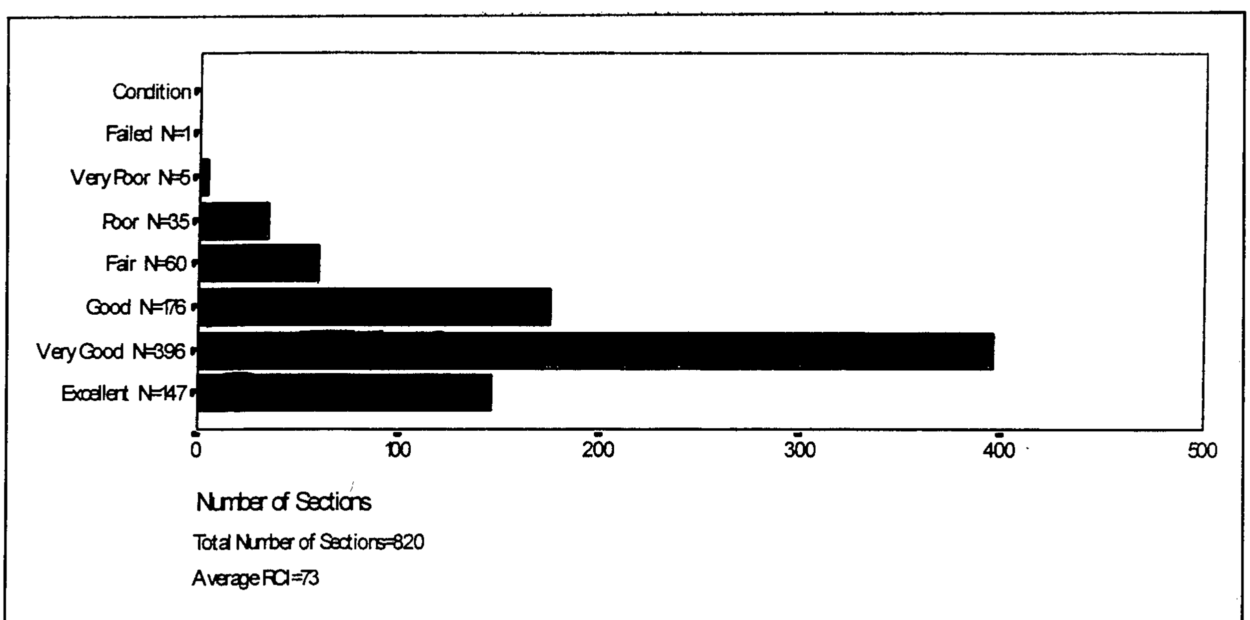


Figure 2. RCI frequency histograms for roof sections 6 to 10 years old.

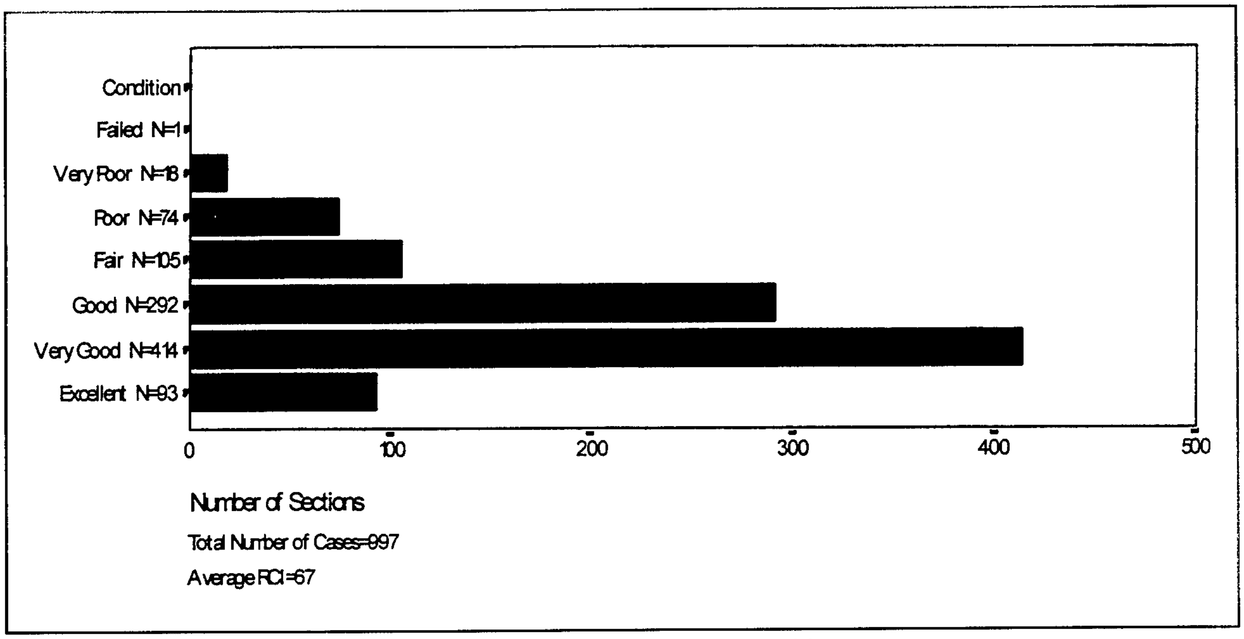


Figure 3. RCI frequency histograms for roof sections 11 to 15 years old.

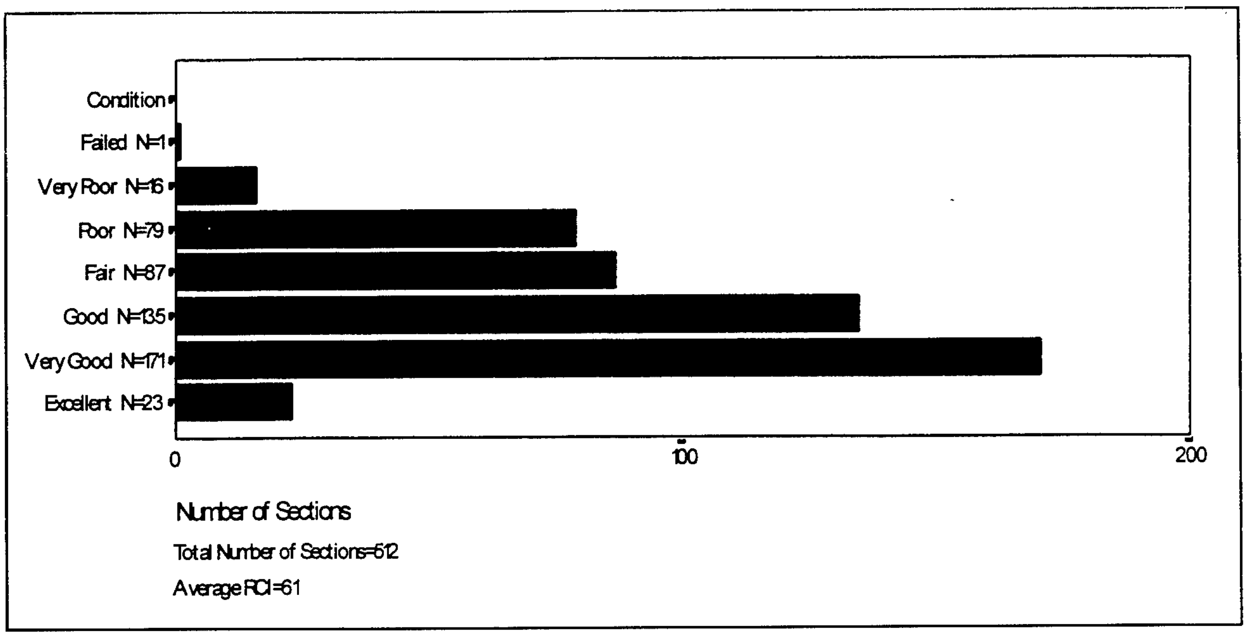


Figure 4. RCI frequency histograms for roof sections 16 to 20 years old.

Table 3. Condition scores and ratings.

Score	0-10	10-25	25-40	40-55	55-70	70-85	85-100
Rating	Failed	Very Poor	Poor	Fair	Good	Very Good	Excellent

concentrated at higher values for newer roofs. The spread of the distribution may be attributed in part to differences in construction and materials, and in part to other uncontrolled variables such as exposure climate.

Frequency Analysis of Design and Construction Factors

In addition to the age of the roof section, numerous additional factors relating to the roof design and construction materials were recorded in the database. A number of these were expected to be related to the condition of a low-slope membrane roof. Notable variables include slope, method of drainage, and type of membrane. To account for nonlinear effects, the roof slope variable was quantized into several categories. This turns out to be important in the analysis. Tables 4-6 present category frequencies for the important roof inventory factors reported in the Micro-ROOFER databases.

General Design

Of the 3059 roof sections, 46 percent were supported by steel structural framing such as beams and girders, trusses, and bar joists (Table 4). Concrete beams or flat slabs provided structural support for 32 percent of the roofs. The large majority of roof decking was non-nailable concrete (39.6 percent), which included precast and cast-in-place decks or steel panels (36.1 percent). Other noncombustible decking included lightweight concrete (5.3 percent) and gypsum fills (4.7 percent). Only 13 percent of the roof sections in the sample had wood decking (97% of which was wood boards and 4% plywood).

Table 4. Descriptive statistics for general design factors.

Variable	Category	Count	Percent
Frame type	Steel	1410	46.1
	Concrete	979	32.0
	Wood	229	7.5
	Unknown	441	14.4
Deck type	Concrete, std	1212	39.6
	Steel	1103	36.1
	Wood boards	275	9.0
	Concrete, lwt	162	5.3
	Gypsum	144	4.7
	Plywood	123	4.0
	Cement fiber	3	0.1
	Missing data	37	1.2
Slope in./ft	0	181	5.9
[grade ratio]	1/8 [1:96]	1089	35.6
	1/4 [1:48]	1221	39.9
Note:	3/8 – 1/2 [1:32 – 1:24]	292	9.5
1 in.=2.54 cm	5/8 – 2 [1:19 – 1:6]	165	5.4
1 ft=30.48 cm	Missing data	111	3.6
Vapor retarder	With vapor retarder	1056	34.5
	Without vapor retarder	1949	63.7
	Missing data	54	1.8
Drainage	With interior drains	1110	36.3
	Without interior drains	1949	63.7

A major design feature, accepted within the roofing industry as a requirement for ensuring satisfactory roof performance, is slope-to-drain. Only 6 percent of the roof sections had no slope for drainage, and about 75 percent had a 1/8 to 1/4 inch per foot slope. Approximately

2/3 of the roof sections used peripheral drainage—expelling rainwater over roof edge or scuppers—instead of through roof drains. Vapor retarders were employed on 1/3 of the roof sections.

Insulation

Roof insulation provides an acceptable substrate for the roofing membrane, reduces energy costs, provides attachment for the membrane, transfers thermal stresses from membrane to deck and in some cases provides slope for drainage. A variety of insulation materials and configurations can be used with membrane roofing. They can be supplied to the job in the form of board stock or a fill material that is poured in place during roof construction. About 40.6 percent of the roof sections were insulated with a single kind of board stock whereas 30.1 percent of the roof sections used board stock in multiple layers of two or more materials (Table 5). For the subject data set, these latter multi-layer systems often employed a foam type board such as polyisocyanurate or expanded polystyrene (EPS) and a recover board such as wood fiberboard or perlite. About 13.4 percent of the roof sections used an insulation fill and 10.7 percent had no insulation. For roofing systems which use more than one insulation material,

Table 5. Descriptive statistics for insulation factors.

Variable	Category	Count	Percent
Insulation config./material	None	327	10.7
	Single material - board	1243	40.6
	Single material - fill	81	2.6
	Combination - all board	920	30.1
	Combination - with board and insul. fill	330	10.8
	Missing data	158	5.2
Insulation material	Polyisocyanurate board	1345	44.0
	Perlite board	1305	42.7
	Polyurethane board	649	21.2
	Glass fiber board	614	20.1
	Wood fiberboard	608	19.9
	Insul. fill - lwt conc.	254	8.3
	Insul. fill - gypsum	140	4.6

Table 6. Descriptive statistics for membrane and flashing factors.

Variable	Category	Count	Percent
Membrane type	BUR - asphalt	2700	88.3
	BUR - coal tar	53	1.7
	EPDM	306	10.0
BUR surfacing	Aggregate	2596	94.3
	Smooth	43	1.5
	Mineral surface cap	32	1.2
	Other	69	2.3
	Missing data	20	0.7
EPDM membrane attachment	Fully adhered	210	68.6
	Loose-laid/ballasted	75	24.5
	Mechanically attached	13	4.2
	Plate/disk partially adh.	5	1.6
	Missing data	3	1.1
Flashing type	With embedded edge metal	2024	66.2
	Without embedded edge metal	1035	33.8
BUR base flashing	Mineral surfaced	1499	54.5
	Reinforced asbestos	388	14.1
	Fibrous glass	272	9.9
	Metal	221	8.0
	Modified bitumen	173	6.3
	None	168	6.1
	Missing data	49	1.8

the Micro ROOFER database design does not provide specific information about the placement of layers.

Of the various insulating materials, polyisocyanurate and perlite boards were the most often used, being present in 44.0 percent and 42.7 percent of the roof sections, respectively. Glass fiber, polyurethane, and wood fiberboard were equally present in the data set; each was found in about 20 percent of the roof sections.

Membrane and Flashing

For the subject data set, 88.3 percent of the roof sections had asphaltic built-up roofing (BUR) membranes, 1.7 percent had coal tar BURs, and the remaining 10 percent were roofed with single-ply EPDM membranes (Table 6). These percentages do not represent the proportions of roofing types found in typical Army membrane roofing inventory. The percentage of BUR is expected to be higher in the current data set than it is across the Army. One reason for this is that not all membrane roofing systems were included in the ROOFER implementations at all 21 of the Army sites analyzed. Also, for sites where ROOFER was implemented before the 1993 completion of the single-ply RCI procedure, only built-up roofing membranes were entered into the inventory database.

For the roof sections having BUR membranes, the ratio of asphalt to coal tar pitch roofs was approximately 50 to 1. The vast majority of the BUR roofs had aggregate surfacing (94.3 percent). The most prevalent base flashings found on these roofs had mineral cap sheet surfacing material (54.5 percent). Reinforced asbestos and fibrous glass base flashing systems were found on 14.1 percent and 9.9 percent of the BURs, respectively.

For the 306 EPDM roof sections, 68.6 percent of the membranes were fully adhered, 24.5 percent were loose-laid and ballasted and 5.8 percent were mechanically attached and/or partially adhered.

Embedded edge-metal flashings existed on two-thirds of the roof sections included in the data set. This percentage held true for both BUR and EPDM, individually.

3 Statistical Model

Model Development

USACERL researchers have developed condition indexes for roof membrane, flashing, and overall condition. Bailey et al. (1989) describes how individual distress data are combined into overall condition indexes for each roof section. In the present study, the condition indexes were taken to be the response variables in linear regression analysis of the ROOFER data. Development of the model entailed the investigation of variables effective for predicting the condition indexes of a roof section.

Factors such as age and type of construction are predictive variables. The fitted model is used to estimate the expected roof condition as a function of the predictive variables. By considering the variation of the observed condition indexes around the values predicted by the model, the uncertainty in the prediction of the condition index also can be estimated.

Model development proceeded in stages. First, analysis of variance (ANOVA) methods were used to test the overall effects on RCI, MCI, and FCI of age, slope, and other factors relating to construction and material types for which information was available. In addition to additive or main effects, interactions between factors were investigated. An interaction occurs if the effect of a factor depends on another factor or combination of factors. In this preliminary stage it was discovered that the effect of roof slope is nonlinear. This nonlinearity was modeled by grouping the slope into several discrete categories and treating these categories as qualitative factors in the model.

After preliminary ANOVA testing of various factors, multiple regression with stepwise variable selection identified variables with the largest impact in the model. Stepwise regression is a technique for systematically entering and deleting variables in the model, building up the model gradually until the variables left out from the model fail to achieve statistical significance. The method is described in standard texts such as Weisberg (1985) and implemented in standard statistical software packages such as SPSS.

Table 7. Estimated effects of predictive variables on condition indexes.

Factor	Value/Category	RCI[1]	MCI	FCI
Age[2]	Age	-1.19/yr (±0.055)	-1.05/yr (±0.062)	-1.27/yr (±0.065)
Membrane Type	Asphalt BUR	ns	ns	ns
	Coal Tar Pitch BUR	ns	ns	ns
	EPDM	+9.52 (±1.51)	ns	+11.66 (±1.78)
Flashing Type	With Embedded Edge Metal	-3.67 (±0.67)	ns	-6.67 (±0.80)
BUR Membrane Surfacing	Aggregate	ns	ns	N/A
	Smooth	-16.97 (±2.30)	-22.63 (±2.62)	N/A
	Mineral Surface Cap	-11.44 (±2.64)	-15.39 (±2.82)	N/A
	Other	ns	-3.26 (±1.49)	N/A
	None	ns	ns	N/A
Drainage	With Interior Drains (vs Without Interior Drains)	-2.92 (±0.69)	-2.72 (±0.73)	-5.11 (±0.82)
Slope	0 in 12 inch	ns	ns	ns
	1/8 in 12 inch	ns	ns	ns
	1/4 in 12 inch	+1.32 (±0.59)	+3.59 (±0.68)	ns
	3/8 to 1/2 in 12 inch	ns	+2.18 (±1.04)	ns
	5/8 to 2 in 12 inch	ns	ns	ns
Deck Type	Steel	-1.80 (±0.67)	ns	N/A
	Concrete, Std	ns	+2.55 (±0.78)	N/A
	Gypsum	ns	ns	N/A
	Concrete, L.W.	-8.94 (±1.18)	-7.99 (±1.36)	N/A
	Cement Fiber	ns	ns	N/A
	Wood Boards	ns	ns	N/A
	Plywood	ns	ns	N/A
Note: Numbers in parentheses are standard errors.				

Table 7. (Cont'd)

Factor	Value/Category	RCI	MCI	FCI
Frame Type	Steel	ns	+2.68 (±0.77)	N/A
	Concrete	-2.33 (±0.69)	ns	N/A
	Wood	ns	ns	N/A
Insulation Type[3]	None	ns	-5.81 (±1.10)	ns
	Open/fibrous	ns	ns	ns
	Closed	+9.51 (±1.65)	ns	+8.94 (±2.00)
	Others	+2.75 (±1.10)	ns	ns
Insulation Type x Membrane Type Interactions	None x Asphalt	ns	ns	ns
	None x Coal Tar Pitch	ns	ns	ns
	Open x Asphalt	+4.25 (±0.89)	ns	ns
	Open x Coal Tar Pitch	ns	ns	ns
	Closed x Asphalt	-4.03 (±1.77)	ns	-8.22 (±2.12)
	Closed x Coal Tar	ns	ns	ns

Notes:
1. + denotes that the variable has a positive relationship with the condition index;
   - denotes that the variable has a negative relationship with the condition index;
   ns (not significant) denotes that the variable has no relationship with the condition index.
2. Age refers to the number of years since the roof was built; in case the roof has been replaced, age refers to the number of years since the roof was replaced.
3. Open/fibrous: Wood Fiberboard, Glass Fiber, Perlite, Expanded Polysty, or Cork.
   Closed: Polyurethane/Board, Extruded Polysty, Foamglass, Phenolic, Polyisocyanurate, or Foamed in place/PUF.

Regression models were developed for RCI, MCI, and FCI separately. Several variables were found to have significant associations with the condition indexes. Table 7 summarizes the results for each of the three models in columns labeled 'RCI,' 'MCI,' and 'FCI.' For each variable the estimated effects are labeled with '+' or '-' if the value has a significant positive or negative effect, whereas the effect is given as 'ns' if it not statistically significant. Certain factors were eliminated on the basis of engineering knowledge and are labeled 'N/A' in the table. Standard errors of the estimates (i.e., estimated standard deviations of the parameter estimates) are given in parentheses. These are computed automatically by the statistical software

using well known formulas. The standard errors are for rough guidance only because variable selection tends to produce standard errors that underestimate the true variation.

The model includes both quantitative and qualitative variables. A quantitative variable such as age enters the model as a linear effect, and its regression parameter is a rate (e.g., the expected rate at which the condition indexes change over time). A qualitative variable such as the type of membrane enters the model as a set of binary (0-1) variables. These indicate which type is present. The number of binary variables required is one less than the number of categories. The reference category is obtained by setting all binary variables to 0. The corresponding regression parameters are increments relative to the reference type (e.g., the expected difference between a built-up asphalt roof and a built-up coal tar pitch roof). An interaction occurs if the increment depends on other variables in the model.

Relations Between Predictive Variables and Condition Indexes

The major findings of the statistical model are summarized below. To interpret the effects of qualitative variables in the model, first note that values labeled 'ns' are combined by the model into a common reference group with no significant differences among them. Values labeled '+' have expected condition index scores significantly higher than those of the values in the reference group, other things being equal. Values labeled '-' have significantly lower expected indexes than values in the reference group. The effect of each variable is adjusted for the other variables in the model. For instance, the estimated differences between membrane types are adjusted for a linear age effect. Overall the model provides a good summary of the trends in the ROOFER data set. However, because the data are observational rather than experimental, any associations found in the model are suggestive rather than proof of causation.

Age

'Age' was the only quantitative variable in the final model. Its estimated effect is given as a yearly rate in the linear model. As expected, 'age' had strong negative associations with all condition indexes. After adjustment for other factors, the downward trend observed in Figures 1-4 remains highly significant. Because the estimated age parameter is a rate, the estimated cumulative effect of age is the product of the parameter estimate and the time period. For instance, over a 10-year

period the RCI is expected to decrease by 12 points; over a 5-year period it is expected to decrease by 6 points.

Membrane and Flashing Type

Compared to roof sections with BUR membranes, sections with EPDM membrane have significantly higher levels of FCI and RCI. Roof sections with different membrane types do not significantly differ from each other with respect to their levels of MCI. For the subject data set, roof sections with embedded edge metal have significantly lower RCIs and FCIs than roof sections without embedded edge metal. Having embedded edge metal versus not having it was found to have no significant effect on MCI.

The FCI and RCI differences between membrane types (asphalt/coal tar BUR versus EPDM) seem to be largely due to an artifact of the RCI procedure—a negative effect of the occurrence of embedded edge metal on the FCIs of BUR roofs. Embedded edge-metal flashings include formed strips of metal placed at the roof edge and continuing down the face of the wall, stripped in with flashing materials. These types of flashings often become the source of roof leaks due to localized splits caused by differential movement of dissimilar materials at the metal joints. Unlike for the single ply flashing evaluation, for BUR the length of embedded edge metal is counted as a low-severity distress and each metal joint within the flashing (i.e., every 10 ft) is counted as 1 ft of medium-severity distress, even when in perfect condition. The reason for this is that maintenance problems commonly arise due to embedded edge metal in BUR membrane roofs.

This discounting of flashing condition by the RCI procedure is a probable cause for the statistically significant interaction between embedded edge metal and age for BUR. BUR roof sections having embedded edge metal appear to start with lower FCIs and RCIs (see Chapter 4 for details). This interaction was not included in the final model because it added little predictive power to the existing model.

It should be noted that in the subject database EPDM roofs are newer, on average, than built-up roofs. Thus, the EPDM effect is partially attributable to other factors such as improvements in building technology, insulation, etc.

BUR Surfacing

BUR surfacing type showed a strong effect on the RCI and MCI. Roof sections with both smooth and mineral surface cap sheet surfacing had much lower indexes than the more prevalent aggregate-surfaced roofs. It is believed that some of this

difference is due to the greater difficulty in visually detecting membrane distresses on aggregate-surfaced BURs.

Drainage

Drainage type has an effect on RCI, MCI, and FCI: roof sections with interior drainage have significantly lower levels of RCI, MCI, and particularly FCI than those without interior drainage.

Slope

Slope has an inverse-U effect on RCI and MCI: roof sections with 1/4 in. in 12 slope have significantly higher RCI than sections with lower or greater levels of slope; sections with 1/4 to 1/2 in. in 12 slope have significantly higher MCI than sections with lower or greater levels of slope. However, slope of the roof has no significant effect on FCI.

Roof Deck Type

Deck type has an effect on RCI and MCI. Roof sections with lightweight concrete fill type of deck have significantly lower levels of RCI and MCI than roof sections with other types of deck. This may be due to insufficient drying of the deck before membrane application or ineffective venting of the roofing system. Either of these may result in the entrapment of water in the overlying insulation and subsequent degradation of the membrane and flashing.

Insulation Type

Roof sections with no insulation have significantly lower levels of MCI than roof sections with insulation. Roof sections with no open-cell foam or fibrous insulation have lower levels of RCI than those with closed-cell foam or fill type of insulation. Roof sections with closed-cell insulation type score significantly higher on FCI than sections with no or other types of insulation. However, due to an interaction (see next section), the effect is negligible if the membrane type is asphalt.

Interactions Between Insulation Type and Membrane Type

Possible interactive effects of insulation type and membrane type were investigated. Specifically, the researchers investigated whether a particular insulation type had a variable effect on RCI, MCI, or FCI depending on the presence or absence of a

particular membrane type. In addition, presence of such interactive effects would imply that the effect of a particular membrane type on the condition indexes depends on the presence or absence of a particular insulation type. It was found that the effect of open-cell/fibrous type of insulation on RCI and closed-cell insulation on RCI and FCI depends on the presence of an asphalt BUR membrane. Similarly, the effect of asphalt BUR membrane type on RCI and FCI depends on the presence of closed- or open-cell insulation type. More specifically, those roof sections that have both open-cell/fibrous insulation and an asphalt BUR membrane have significantly higher RCI than roof sections with other combinations of insulation and membrane types. However, roof sections that have both closed-cell insulation and an asphalt membrane have significantly lower RCI and FCI than sections with other combinations of insulation and membrane types.

Variation Between Installations

The Army Installation label was entered as a categorical factor in the model. Some variation between installations can be attributed to various uncontrolled factors including climate, nominal levels of design and construction quality, repair and maintenance budgeting, etc. For prediction purposes, the model includes a base-specific constant term. This is the average estimated score at age zero after adjustment for the construction and material factors. These base-specific constants are given in Table 8. As explained in the next section, these constants are used as baseline parameters in the prediction of the roof condition at a specific installation.

Proportion of Variance

R-squared is a commonly used summary statistic describing the effectiveness of the model in explaining the variation in the response variable. It is the ratio of two sums-of-squares: the sum-of-squared devi-

Table 8. Base-specific constants for the regression model.

Base	RCI	MCI	FCI
Fort A	95.55	100.00	100.00
Fort B	94.60	100.00	94.05
Fort C	93.54	100.00	97.56
Fort D	88.47	100.00	92.68
Fort E	84.18	96.43	100.00
Fort F	84.16	100.00	100.00
Fort G	84.16	100.00	86.24
Fort H	84.16	100.00	86.30
Fort I	84.16	88.11	94.22
Fort J	84.16	91.35	86.25
Fort K	84.15	84.78	93.30
Fort L	84.15	100.00	86.25
Fort M	84.15	88.65	86.29
Fort N	81.60	89.63	86.27
Fort O	81.26	80.46	86.27
Fort P	79.86	89.08	86.27
Fort Q	76.78	84.01	78.80
Fort R	75.07	87.76	76.53
Fort S	74.27	83.93	86.28
Fort T	66.46	85.81	59.72
Fort U	63.10	100.00	50.43

ations of the predicted values about the mean response; and the sum-of-squared deviations of the responses about the mean response. Converting this ratio to a percentage leads to the percentage of variation explained by the model. For the subject data set the fitted models for RCI, MCI, and FCI explain 61 percent, 54 percent, and 60 percent of the variation respectively. For additional information on the R-squared statistic see, for example, Draper and Smith (1981).

Cross-Validation Estimates of Prediction

Stepwise selection includes variables on the basis of their apparent statistical significance. The reported significance levels of the variable selected tend to be overstated; see, for example, Weisberg (1985, Chapter 8). A closely related problem is that the reported estimate of residual standard deviation may underestimate the true residual standard deviation. It is therefore important to investigate both the stability of the variable-selection process and the reliability of the estimate of residual standard deviation. Note that the residual standard deviation is an important component of the uncertainty estimate for a model-based prediction.

A CV analysis was undertaken to investigate these issues for the subject data set. In the CV analysis the data were split into two subsets randomly: (1) a training set used for developing the statistical model and (2) a test or validation set used to assess the precision of the model-based predictions. After developing the models on the training data only, the models are used to predict the condition indexes RCI, MCI and FCI for the data in the test set. To estimate the prediction error, the root mean square (RMS) error of the predictions was computed independent of the model. For comparison, the model-based RMS residual from the training data was also computed. This would be the usual residual uncertainty estimate if training data were the only data available. If these two measures are close to each other, one would be confident that the model-based uncertainty estimate is reliable. In general, one can expect that the model-based estimate is biased by the variable selection. Typically the model-based estimate is too small. The CV estimate is more reliable because the error estimate is based on data that were not used for modeling. For further details see Weisberg (1985).

Table 9 summarizes the results of the cross-validation study. The table compares mean square residual and cross-validation (CV) estimates of predictive error. The root mean square error (RMSE) gives a measure of predictive

Table 9. Estimates of RMS prediction error.

	RCI	MCI	FCI
Test set (CV)	14.0	15.7	17.2
Training set (RMSE)	13.8	15.5	16.2
Full data (RMSE)	13.7	15.4	16.5

accuracy comparable to the standard deviation as a measure of estimation accuracy. Any bias in the model-based uncertainty estimates is small. Also note that, although the model accounts for a substantial portion of the variation in condition index values among roof sections, the estimated RMS prediction error ranges from ±14 for RCI to ±17 for FCI. These numbers give rough estimates of the prediction error in the model. One would expect roughly two-thirds of the RCI values to be within 14 points of the values predicted by the model and roughly 95 percent to be within 28 points of the predicted value. Clearly there remains considerable variation beyond what is accounted for by the predictive variables.

Predictive Model

The statistical models developed from the data set provide the means for estimating or predicting RCI, MCI, and FCI from the age and design and construction factors. The error estimates previously discussed in this chapter provide guidelines concerning the uncertainty of the predictions. This following text demonstrates the use of a predictive model. The model assumes the expected condition index of a roof section depends linearly on the roof's age, but it adjusts for other factors found to be significant in the model-development stage. Linearity of the age effect appears to be a reasonable assumption except for the earliest years of roof life. Chapter 4 provides further information on this aspect.

To demonstrate the use of the predictive model, consider a hypothetical roof section 10 years old and located on the Fort D installation. Table 7 provides the parameter estimates necessary to predict RCI, MCI, and FCI for the roof section given specified values of the design and construction variables. These parameter estimates enter Table 10 as adjustments to the predicted condition index. Summing the adjustments leads to the predicted RCI, MCI, and FCI for the hypothetical roof section. These are reported in the last row of the table.

The reported uncertainty estimates are from the CV analysis discussed in the preceding section. The numbers in parentheses are estimated standard deviations about the predicted value. The actual value would be expected to lie within one standard deviation of the predicted value two-thirds of the time, and the actual value would be expected to fall within two standard deviations of the predicted value 95 percent of the time.

Another use of the predictive model is to investigate the impacts of changes in design. In the current hypothetical example, suppose coal tar pitch is used instead of asphalt membrane, with other design variables kept the same. Then the

Table 10. Predicting RCI, MCI, and FCI for a hypothetical roof section.

Variable	Value	RCI Adjustment	MCI Adjustment	FCI Adjustment
Baseline	Fort D	88.47	100.00	92.68
Age	10 Years	-1.19*10= -11.9	-1.05*10= -10.5	-1.27*10= -12.7
Membrane	Asphalt	0	0	0
Edge Metal	None	0	0	0
Membrane Surfacing	Mineral Surf. Cap.	-11.44	-15.39	0
Int. Drain	None	0	0	0
Slope	1/4 in 12"	1.32	3.59	0
Deck	Concrete	0	2.55	0
Frame	Steel	0	2.68	0
Insulation	Closed	9.51	0	8.94
Insulation x Membrane	Closed x Asphalt	-4.03	0	-8.22
Predicted	Sum	71.9 (±14.0)	82.9 (±15.7)	80.7 (±17.2)

expected RCI increases by 4.03 to 75.9. The difference occurs because of the negative interaction between closed-cell insulation and asphalt, which is absent if asphalt is replaced with coal tar pitch.

The user should be aware that the predictions depend on the modeling assumptions, such as linearity of the age effect and constancy of various adjustment factors across levels of other factors. In addition, because the data are observational rather than experimental, the predictive model is advisory only. The advantages of the linear predictive model are that many factors can be investigated, and the model provides initial estimates for extrapolation to hypothetical roofs beyond the domain of the roofing data at hand. Chapter 4 discusses a complementary, semi-parametric approach to predictive modeling which assumes only that the age-degradation curve is smooth and monotone.

4 Quantile Plots and Degradation Curve Development

To show how individual design and construction factors affect the rate of change of the condition indexes over time, Figures 5 and 6 include the 25th, 50th, and 75th percentile curves of RCI for two different factors: flashing type and drainage type. Only BUR sections are included in the scatter plots and in the calculation of quantiles.

The percentile curves are calculated based on the notion of regression quantiles (Koenker and Bassett 1978), but without assuming linearity. Each percentile function is approximated by a quadratic spline on a set of uniform knots. The number of internal knots (typically zero or one in these applications) is determined adaptively to balance the fidelity to data and the complexity of the model. A more detailed description of the quantile splines can be found in He and Shi (1994).

In calculating the percentile curves, the researchers incorporated the constraints that each percentile curve is non-increasing in time and that all

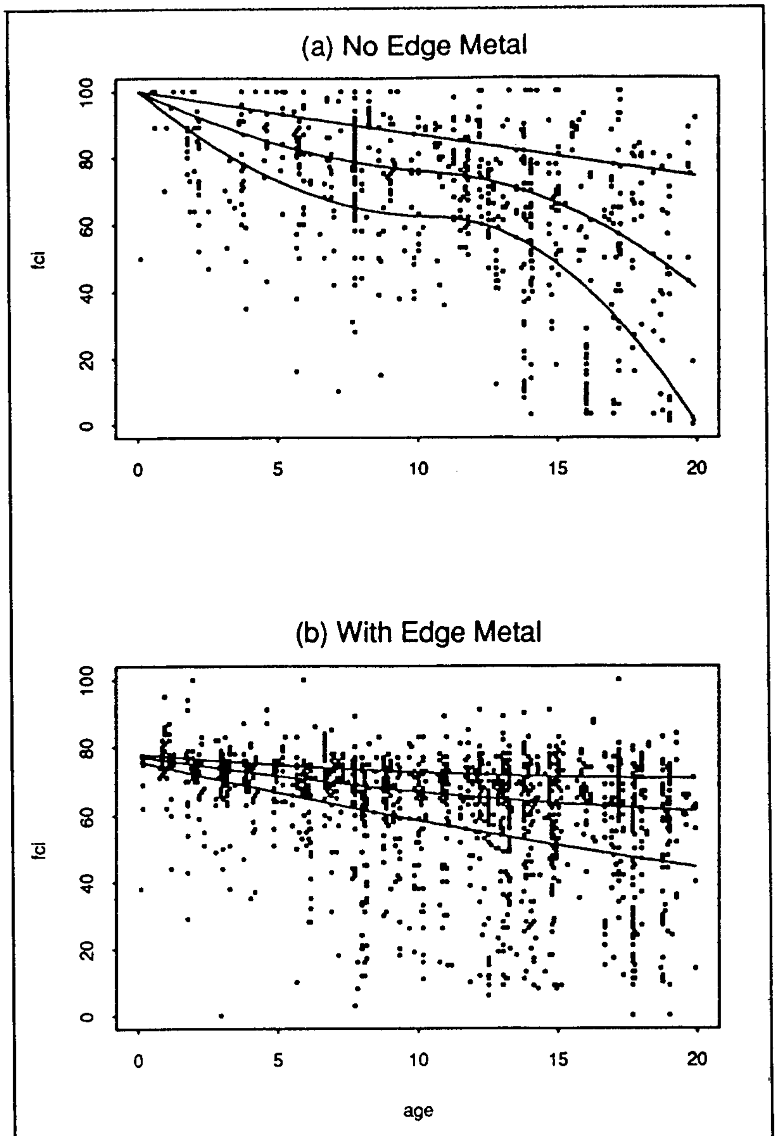


Figure 5. FCI quartiles by flashing type.

curves are bounded by the maximum value 100. Except for Figure 5(b), the percentile curves are assumed to start at 100 for new roof sections. Figure 5(b) pertains to roof sections with embedded edge metal. Such roofs are evaluated with lower RCI for new roofs, as described in Chapter 3 under "Membrane and Flashing Type." The constrained quantile splines shown in these figures were computed using constrained B-spline curve-fitting software (COBS), which was developed for S-Plus (MathSoft, Inc., 101 Main St., Cambridge, MA 02142-1521). Documentation and the latest version of COBS may be obtained at the World Wide Web site http://ux6.cso.uiuc.edu/~x-he/ftp.html.

Examination of these quantile plots can provide additional insights. They suggest that the variability in the conditions typically increases with age. As an example of a specific finding, embedded edge metal is found to be a negative factor in the regression analysis, as reported in Chapter 3, but Figure 5 suggests that interaction between flashing type and age exists. The condition of roofs with embedded edge metals actually holds up comparatively well as one looks beyond 10 years.

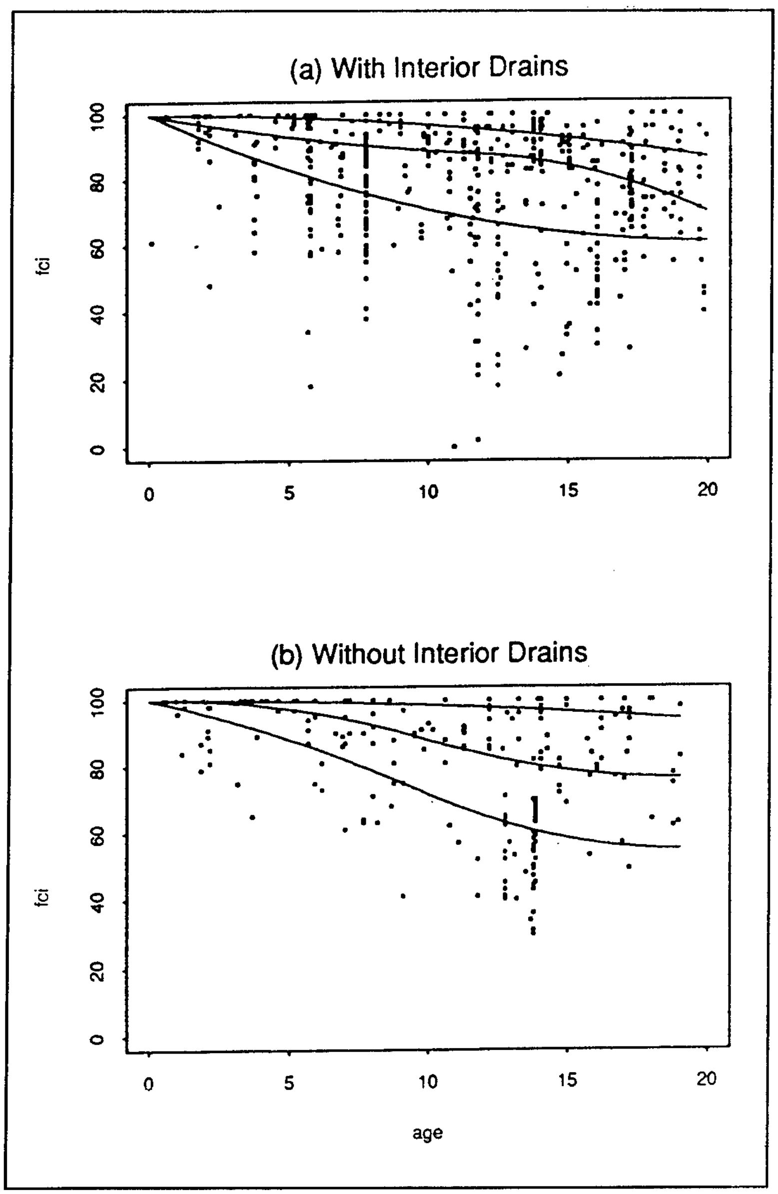


Figure 6. MCI quartiles by drainage type.

5 Summary and Recommendations

Summary

This report has presented a statistical analysis of a consolidated MicroROOFER database comprising inventory and inspection data for 3059 roof sections at 21 Army installations. The researchers employed ROOFER condition indexes as response variables in a large-scale regression analysis. The goal was to identify important factors influencing roof deterioration over time and also to provide a conceptual model with uncertainty estimates for predicting roof condition as a function of age.

Among the most important factors identified in the analysis are membrane and flashing types, membrane surfacing, and drainage. In addition, a moderate slope was found to be a positive factor, and lightweight concrete fill deck was found to be a negative factor. By far the most important predictor was age. Degradation curves provide expected percentiles as a function of age, after adjusting for various design and construction variables.

The predictive models and degradation curve methodology presented in this report can provide the means for predicting how a particular roof section is likely to degrade over time, and also to indicate the range of values of condition indexes that are likely to occur.

Recommendations

It is recommended that investigations be conducted to develop enhanced RCI prediction models based on the degradation curve methodology developed in this study. Families of curves should be developed for design and construction factors determined to be significant in predicting roof condition.

References

Bailey, D.M., D.E. Brotherson, W. Tobiasson, and A. Knehans, *ROOFER: An Engineered Management System (EMS) for Bituminous Built-Up Roofs*, Technical Report M-90/04/ ADA218529 (U.S. Army Construction Engineering Laboratory [USACERL], December 1989).

Bailey, D.M., D.E. Brotherson, W. Tobiasson, S. Foltz, and A. Knehans, *ROOFER: Membrane and Flashing Condition Indexes for Single-Ply Membrane Roofs — Inspection and Distress Manual*, Technical Report FM-93/11/ADA272573 (USACERL, April 1993).

Draper, N., and H. Smith, *Applied Regression Analysis*, 2d ed. (John Wiley & Sons, Inc., 1981).

He, X., and P. Shi, "Convergence Rate of B-spline Estimators of Nonparametric Conditional Quantile Functions," *Journal of Nonparametric Statistics* (1994), pp 299-308.

Koenker, R., and G. Bassett, "Regression Quantiles," *Econometrica* (1978), pp 33-50).

Shahin, Mohamed Y., David M. Bailey, and Donald E. Brotherson, *Membrane and Flashing Condition Indexes for Built-Up Roofs, Volume II: Inspection and Distress Manual*, Technical Report M-87/13 v II/ADA190368 (USACERL, September 1987).

Weisberg, S., *Applied Linear Regression*, 2d ed. (John Wiley & Sons, Inc., 1985).

USACERL DISTRIBUTION

Chief of Engineers
ATTN: CEHEC-IM-LH (2)
ATTN: CEHEC-IM-LP (2)
ATTN: CECG
ATTN: CECC-P
ATTN: CECC-R
ATTN: CECW
ATTN: CECW-O
ATTN: CECW-P
ATTN: CECW-PR
ATTN: CEMP
ATTN: CEMP-E
ATTN: CEMP-C
ATTN: CEMP-M
ATTN: CEMP-R
ATTN: CERD-C
ATTN: CERD-ZA
ATTN: CERD-L
ATTN: CERD-M (2)
ATTN: DAIM-FDP

CECPW 22310-3862
ATTN: CECPW-E
ATTN: CECPW-FT
ATTN: CECPW-ZC

US Army Engr District
ATTN: Library (40)

US Army Engr Division
ATTN: Library (11)

US Army Europe
ATTN: AEAEN-EH 09014
ATTN: AEAEN-ODCS 09014
29th Area Support Group
ATTN: AEUSG-K-E 09054
222d BSB Unit #23746
ATTN: AETV-BHR-E 09034
235th BSB Unit #28614
ATTN: AETV-WG-AM 09177
293d BSB Unit #29901
ATTN: AEUSG-MA-E 09086
409th Support Battalion (Base)
ATTN: AETTG-DPW 09114
412th Base Support Battalion 09630
ATTN: Unit 31401
221st Base Support Battalion
ATTN: Unit 29623 09096
CMTC Hohenfels 09173
ATTN: AETTH-SB-DPW
Mainz Germany 09185
ATTN: AETV-MNZ-E
21st Support Command
ATTN: DPW (8)
SETAF
ATTN: AESE-EN-D 09613
ATTN: AESE-EN 09630
Supreme Allied Command
ATTN: ACSGEB 09703
ATTN: SHIHB/ENGR 09705

INSCOM
ATTN: IALOG-I 22060
ATTN: IAV-DPW 22186

USA TACOM 48397-5000
ATTN: AMSTA-XE

Defense Distribution Region East
ATTN: ASCE-WI 17070-5001

Defense Distribution Region West
ATTN: ASCW-WG 95296-0100

HQ XVIII Airborne Corps 28307
ATTN: AFZA-DPW-EE

American Public Works Assoc. 64104-1806

US Army Materiel Command (AMC)
ATTN: AMCEN-F 22333-0001
ATTN: AMXEN-C 61299-7190
Installations: (20)

4th Infantry Div (MECH) 80913-5000
ATTN: AFZC-FE

FORSCOM
ATTN: FCEN 30330
Installations: (20)

6th Infantry Division (Light)
ATTN: APVR-DE 99505
ATTN: APVR-WF-DE 99703

TRADOC
Fort Monroe 23651
ATTN: ATBO-G
Installations: (20)

Fort Belvoir 22060
ATTN: CETEC-IM-T
ATTN: CETEC-ES 22315-3803
ATTN: Water Resources Support Ctr

USA Natick RD&E Center 01760
ATTN: STRNC-DT
ATTN: AMSSC-S-IMI

US Army Materials Tech Lab
ATTN: SLCMT-DPW 02172

USARPAC 96858
ATTN: DPW
ATTN: APEN-A

SHAPE 09705
ATTN: Infrastructure Branch LANDA

Area Engineer, AEDC-Area Office
Arnold Air Force Station, TN 37389

HQ USEUCOM 09128
ATTN: ECJ4-EN

CEWES 39180
ATTN: Library

CECRL 03755
ATTN: Library

USA AMCOM
ATTN: Facilities Engr 21719
ATTN: AMSMC-EH 61299
ATTN: Facilities Engr (3) 85613

USAARMC 40121
ATTN: ATZIC-EHA

Military Traffic Mgmt Command
ATTN: MT-LOF 22041-5000
ATTN: MTE-SU-FE 28461

Fort Leonard Wood 65473
ATTN: ATSE-DAC-LB (3)
ATTN: ATZT
ATTN: ATSE-CFLO
ATTN: ATSE-DAC-FL
ATTN: Australian Liaison Office

Military Dist of WASH
ATTN: ANEN-IS 20319

USA Engr Activity, Capital Area
ATTN: Library 22211

US Army ARDEC 07806-5000
ATTN: AMSTA-AR-IMC

Engr Societies Library
ATTN: Acquisitions 10017

US EPA, Region V
ATTN: AFRC-ENIL-FE 60561

US Army Environmental Center
ATTN: SFIM-AEC-NR 21010
ATTN: SFIM-AEC-CR 64152
ATTN: SFIM-AEC-SR 30335-6801
ATTN: AFIM-AEC-WR 80022-2108

Defense Nuclear Agency
ATTN: NADS 20305

Defense Logistics Agency
ATTN: MMDIS 22060-6221

National Guard Bureau 20310
ATTN: NGB-ARI

US Military Academy 10996
ATTN: MAEN-A
ATTN: Facilities Engineer
ATTN: Geography & Envr Engrg

Naval Facilities Engr Command
ATTN: Facilities Engr Command (8)
ATTN: Engrg Field Offices (11)
ATTN: Public Works Center (8)
ATTN: Naval Constr Battalion Ctr 93043
ATTN: Naval Facil. Engr. Service Ctr 93043-4328

8th US Army Korea
ATTN: DPW (11)

USA Japan (USARJ)
ATTN: APAJ-EN-ES 96343
ATTN: HONSHU 96343
ATTN: DPW-Okinawa 96376

416th Engineer Command 60623
ATTN: Gibson USAR Ctr

US Army MEDCOM
ATTN: MCFA 78234-6000
Fort Detrick 21702-5000
ATTN: MCHS-IS
Fort Sam Houston 78234-5000
ATTN: MCFA-PW
Walter Reed Army Medical Center 20007-5001
ATTN: MCHL-PW

Tyndall AFB 32403
ATTN: HQAFCESA/CES
ATTN: Engrg & Srvc Lab

USA TSARCOM 63120
ATTN: STSAS-F

US Army CHPPM
ATTN: MCHB-DE 21010

US Gov't Printing Office 20401
ATTN: Rec Sec/Deposit Sec (2)

Nat'l Institute of Standards & Tech
ATTN: Library 20899

Defense General Supply Center
ATTN: DGSC-WI 23297-5000

Defense Construction Supply Center
ATTN: DCSC-WI 43216-5000

Defense Tech Info Center 22060-6218
ATTN: DTIC-O (2)

276
1/97